Getting ahead or falling behind? – The importance of households' ability to manage idiosyncratic risk in rural Ghana

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Introduction

Identifying who moves in and out of poverty over time has been the focus of a growing literature on household level poverty dynamics. A central theme of this literature has been the role of shocks and their impact on households' ex ante and ex post risk management strategies. Shocks and strategies to mitigate their impact affect household level welfare dynamics. Success or failure to prevent and to deal with shocks determines whether households are able to escape and remain out of poverty or whether they continue to be or become poor as a result of adverse events. In turn, this success and failure is determined by households' ability to access effective insurance mechanisms, both formal and informal. The more effective and accessible these mechanisms are the greater is the chance to recover from negative shocks and to improve well-being over time. Conversely, households with limited access to any type of insurance mechanism will find it harder to weather shocks and avoid chronic poverty. Yet while these conceptual points are well understood, the literature is strikingly thin on empirical evidence on both the impact of shocks on household welfare dynamics and, especially, the potentially differential effectiveness of alternative risk management mechanisms in mediating those dynamic welfare effects.

It is useful to distinguish between two broadly different types of risk to which households are exposed. Covariate risk, such as drought, rainfall, pests or civil war, affect most or all of a population, albeit not always equally. As a consequence, efforts to deal with covariate risk have to look beyond the geographic location or subject population and focus on risk pooling across larger areas and populations. Covariate risks have been the focus of much of the existing literature (Rosenzweig 1988; Hoddinott and Kinsey 2001; Dercon 2004; Newhouse 2005; Alderman *et al.* 2006; Hoddinott 2006).

Despite the predominant focus in the welfare dynamics literature on covariate risk, a growing body of evidence suggests that idiosyncratic risk often dominates covariate risk. Townsend (1994) finds this in rural India. Deaton's (1997) and Kazianga and Udry's (2006) results corroborate this for South Africa and Burkina Faso. Lybbert et al. (2004) find that this even holds among pastoralists in southern Ethiopia, a population that is subject to highly covariate rain, epidemiological and range ecological shocks. Similarly, our survey and focus groups from rural Ghana suggest that covariate shocks were few during the study period 1997 to 2009 but indicated numerous household-specific shocks, as we describe below.

Unlike covariate risk exposure to idiosyncratic shocks can, in principle, be readily managed within a population or location. The largely unanswered empirical question that remains is which types of local risk management mechanisms are available and effective in mitigating exposure to idiosyncratic risk and/or the impact of idiosyncratic shocks. One key and novel contribution of our paper is, therefore, to focus on household-specific risk and its impact on household- level welfare dynamics. The main questions we address in this paper is how idiosyncratic shocks affect welfare path dynamics and whether those effects are mitigated differentially by different risk management strategies.

Households employ a range of strategies to minimize their ex ante exposure to risk and to smooth their consumption over time ex post of realized shocks. Autarkic households might be able to self-insure through savings. Others may have access to informal and formal insurance and credit, social networks, labor markets offering alternative employment, and/or income diversification. Existing studies focus on any one, or at most two, of these insurance mechanisms. In this paper, for the first time, we compare among them simultaneously.

Households employ available risk management mechanisms in order to maximize their welfare by smoothing their consumption over time. Insurance can come from a variety of sources: self-insurance and asset accumulation through own savings (Dercon 1998; Kazianga and Udry 2006), selling buffer stocks (Lim and Townsend 1998), pre-cautionary savings (Kimball 1990; Carroll 1998), or through selling assets and livestock. However, households typically cannot fully insure against fluctuations in income. Hence, they are forced to adopt coping strategies that reduce their welfare temporarily or permanently, for instance, by selling off important productive assets such as bullocks in India (Rosenzweig and Wolpin 1993, McPeak 2004), taking children out of school or by having to drop their food consumption to levels that cause irreversible damage to children's growth and development (Alderman *et al.* 2006, Hoddinott 2006).

Social networks provide another mechanism to mitigate the effect of idiosyncratic shocks. Social visibility can affect welfare dynamics in at least six ways. It can prevent asset decumulation post shock, mitigate the need for precautionary, liquid savings for self-insurance, foster productivity growth through ex ante risk management, improve social learning about promising employment, marketing or technological opportunities, enhance the security of land tenure, and facilitate access to micro credit based on group lending principles. Through any or all of these mechanisms, social visibility may affect the asset accumulation path followed by households by increasing the expected net returns to assets, reducing asset risk, or both. Vanderpuye-Orgle and Barrett (2009) examine the importance of social networks in managing risk for households in rural Ghana. They find that those who are socially invisible and who suffer a farm shock or theft - idiosyncratic shocks that are typically informally insured among the socially visible - are unable to smooth consumption effectively while otherwise identical persons who are socially visible have near-complete consumption smoothing.

Diversification of income sources represents another informal mechanism to insure against risk. Where formal insurance access is limited, as is the case in most rural areas, income diversification is the norm rather than the exception (Reardon 1997, Barrett et al. 2001, Davis et al. 2010). The reasons for households to diversify their income are multiple. For some households diversification may be driven by necessity and to ensure survival. The expected return to a diversified portfolio of low-return crops may be lower than for a single high-risk and higher return crop but when other types of insurance mechanisms are weak household may nonetheless choose the former. Or households may be forced to enter other income generating activities as a consequence of negative shocks. In contrast, other, typically better-off households may be prompted to diversify out of choice either by trying to get the highest return to their investment by combining several high-return activities, or in order to strategically accumulate assets as they move from farm to non-farm activities and as they prepare to and then migrate to cities (Ellis 1998, 2000a and 2000b, Barrett e*t al*. 2001).

Our paper goes beyond the existing studies by examining each of these risk management strategies individually as well as jointly. This allows us to both assess the relative importance of these mechanisms as well as identify prospective complementarities between them. This extension beyond an individual risk management mechanism allows a more appropriate modeling of the behavior of households that face risk as when one or more risk management mechanisms are unavailable households resort to other mechanisms. Evidence from rural Pakistan, for example, suggests that interpersonal transfers partially make up for missing access to formal financial institutions (Behrman *et al.* 1997).

Context: The four villages, 1998-2009

The four communities studied in this paper are located in Akwapim South district, a hilly rural area in southern Ghana. The study area is less than 30 miles from Ghana's capital city, Accra, but too far for community members to regularly commute for work. The four communities are large villages, or clusters of smaller villages, with estimated populations of between 700 and 2,500. They were selected in 1997-98 for a study of farmers' decisions to start pineapple farming for export (Udry and Goldstein 1999). Two of the communities lie on sealed roads and close to small towns, while the others are in a remote valley on unsealed roads. Since the communities were selected purposively to provide a representation of the range of economic conditions in the district, their economic and social characteristics are quite different. Nevertheless, all four communities are within the same geographic region and climatic zone, have a common history, and share the same central markets.

The patterns of employment and economic activity in the communities align closely with their geographic characteristics. In the two more remote communities, most households are employed in farming. Some of this farming is commercial, the bulk of which is growing pineapple for export or domestic processing (Conley and Udry 2010). Most of the remaining produce grown is consumed within the household, with any surpluses being sold on the street or in town markets. In the other two communities, there are fewer farmers and more wage workers. Some of these are employed by the government and local businesses; the remainder are self-employed in occupations like taxi driving and hairdressing.

The economic situation in these communities has evolved, and continues to evolve, at a rapid pace. In the decades following World War II, the area was central to Ghana's cocoa industry, but over time this industry has declined. In the early to mid 1990s, the area was the epicenter of Ghana's nascent export pineapple industry. Through the late 1990s and early 2000s, the export industry boomed, migrants came to the communities to work in the fields, and in the case of at least one of the communities, almost everyone was involved in pineapple cultivation in some way (Fold and Gough 2008). However, a rapid change in market conditions in Europe around 2005 dramatically cut demand for Ghanaian pineapples. Between 2005 and 2009 many farmers in the study area abandoned pineapple cultivation and, in some cases, migrated out of the community. Since contracts were often made by word-of-mouth, farmers had no guarantee of payment by the buying companies. Payments were often made months after delivery (Fold and Gough 2008, pp. 1692-93). Accordingly, there are numerous cases in our data of farmers reporting large contract defaults, with amounts unpaid sometimes running into the thousands of dollars. In the years since 2005, many people in the study area have moved on to other livelihoods, or adapted to the new export market conditions. Anecdotally, however, the shock had a significant impact on the welfare of the community. In the analysis below, we will examine how households coped with this and other others they faced in the decade prior to 2009.

Another recent economic change has been the encroachment of urban areas. In two of the communities, nearby town centers have expanded, and demand for rented housing and (in the case of one community) land for housing has pushed up the price of land. This, too, has caused a shift in land use patterns, with some farmers in that community selling almost all of their land and shifting to wage work or semi-retirement (Hardiman 2003).

Aside from these shocks, the community members reported in pre-survey meetings and post-survey focus group interviews that there were no significant common shocks during the last decade. Agricultural conditions have been within the normal range of fluctuation, and the political situation has been stable (with only one peaceful change of government, in 2009). There have been no notable animal, human or plant disease epidemics, although individual cases of malaria, dysentery and other ailments remain common.

Although the district has been occupied by a single ethnic group, the Akwapim, for over 200 years, migration is commonplace. Individuals migrate to towns and cities in search of work, or to join their spouse's family after marriage, and a number of households reported holding land in different regions of Ghana. In our sample, around 17 percent of respondents had migrated from another region to live permanently in the study area. Since land is held in family and clan lineages, and land sales are rare, migrants typically rent land for farming.

Since most households do not satisfy the criteria to access formal lending sources or insurance, individuals rely on their own savings, and on each other, to cope with shocks (Walker 2011). There are two main sources of support used by community members: family and friendship networks, and mutual assistance groups. We will briefly describe these in turn – first, the structure of the household and patterns of exchange therein, and second, the main sources of support from other households.

Families in the district are interdependent and exchange gifts and loans in order to help cope with shocks. Individuals live in compounds, a conglomerate of houses containing more than one household (typically linked by kinship). A few men continue to practice traditional polygamy, with each wife and her descendants usually living separately. For the purposes of this study, we treat such families as one household unit.

It is traditional in the study area for men to be the main breadwinners and to be responsible for covering the cost of food and household supplies. However, men and women often maintain separate finances. Previous research has established that spouses do not fully share information on their farming activities or earnings (Goldstein *et al.* 2002, Boozer *et al*. 2009). Reflecting this, they do not appear to fully insure each other against income shocks. Using earlier household survey data from these communities, Goldstein (1999) was able to reject risk-sharing at the intrahousehold level. In part, this may be due to the relative rarity of large shocks idiosyncratic to just one spouse. For large shocks, individuals often turn to their extended family and friends for support.

Informal and religious groups are common in the study communities, and these groups play a substantial role in the system of informal support. Foremost, a majority of individuals actively attend religious ceremonies, at churches or mosques. Religions are diverse in the communities and there is widespread tolerance between religions. Individual religious groups have strong ethics of sharing and mutual support, typically extending aid to families in need and raising funds from community members for charity within the village and elsewhere.

Individuals are also commonly involved in farmers' groups or other support groups, which may provide assistance to those in need in the form of labor, finance or training. Of our respondents, 45 percent reported being a member of at least one support group of some sort, and 18 percent a member of a church group. Individuals in our study reported joining such groups in search of assistance, and reported receiving help from these networks in times of need. Such groups may also form the basis of friendship links that are used for mutual insurance. Indeed, while Goldstein (1999) was able to reject the hypothesis of intrahousehold insurance in these communities, he was unable to reject the hypothesis of risk sharing between village members of the same gender, suggesting that gender-specific groups may be operating effectively as coinsurance networks.

Data

Our data were collected in the Akwapim South District in rural Eastern Ghana and cover the period between 1998 and 2009. The first wave of the panel was collected in 1997-98 (Udry and Goldstein 1999). For the 2009 wave we revisited as many of the original 212 households as possible. A substantial number of these households no longer existed, and for those that did the data do not contain all necessary variable for both years. Attrition and non-availability of variables reduces our sample size by 34%. This results in a useable panel of 135 households

The dataset we use in this paper summarizes data at the household level. The 2009 wave was administered in five rounds. Where appropriate we average values over the five rounds, for example, in compiling the consumption data.

Consumption aggregates were constructed by household and then divided by household size in per adult equivalents. Household consumption includes all expenditures other than a set of lumpy items or items that do not contribute to the level of well-being, including health expenditures, purchases of financial assets, marriage and dowry expenses, purchases of furniture, appliances, mobile phones, bicycles, motor vehicles, as well as court fees, gifts and transfers, funeral and birthday expenses and house and land rents. All monthly household expenditures as well as the assets expressed in currency were deflated by the CPI and converted into 2009 Ghanaian Cedi.

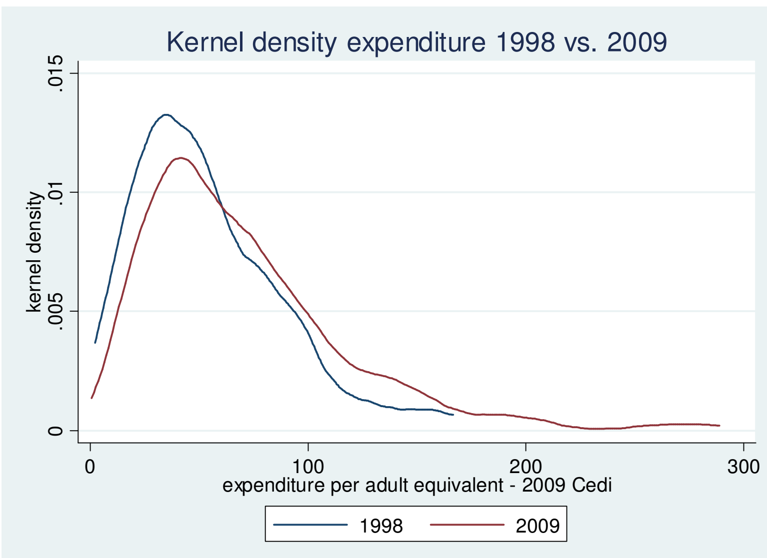
Table 1 Household expenditure per adult equivalent (2009 Cedi and US$)

	1998		2009	
	Cedi per month	US$ per day	Cedi per month	US$ per day
Darmang	55.49	1.28	58.11	1.34
Pokrom	64.33	1.48	54.53	1.25
Oboadaka	54.75	1.26	53.15	1.22
Konkunuru	63.21	1.45	68.95	1.59
All villages	59.23	1.36	58.92	1.35

Table 1 shows that for the villages as a whole, monthly expenditure levels have remained almost constant between 1998 and 2009 at around 59 Cedi per adult equivalent, equivalent to roughly US$1.35 per day at 2009 prices. Underlying this overall stagnant trend are divergent patterns across villages. Expenditure levels rose slightly in Darmang and Konkonuru whereas they fell in Pokrom and very slightly in Oboadaka. This pattern likely reflects the fact that Konkunuru and Darmang are characterized by more dynamic economies with better infrastructure and that these two villages have significantly reduced their dependence on agricultural livelihoods and become more urbanized over the study period.

The empirical distributions in Figure 1 for household expenditure per adult equivalent for the whole sample show a right-ward shift between 1998 and 2009. This suggests a slight improvement in expenditure levels, which seemingly contradicts the figure in Table 1. However, the averages in Table 1 are partly driven by a few large outliers. For example, if we take out of the sample the three richest households that have per monthly adult equivalent expenditure greater than 300 Cedis[1], then average expenditure levels for the remaining households increased from 54.1 Cedis in 1998 to 57.8 Cedis in 2009.

Figure 1 Kernel density of expenditure



e(sample) only

The empirical analysis below includes a number of household level control variables. The age and sex of the household head control for lifecycle and gender effects. Whether the respondent or his/her parents have held a village office, whether the respondent is the first in the family to live in the village and whether he/she had previously been in foster care act as a proxy for the social status in the village and for the strength of social networks over and above the degree of social visibility discussed below.

To examine the role of different sources of idiosyncratic risk on household welfare dynamics we designed the shocks module of the 2009 survey to ask for detailed recall information on the frequency and the monetary value of 20 negative and 9 positive shocks that may have affected the household since the first wave of the panel in 1998. This creates a large number of variables. For instance, for the typical household with two respondents and 12 years of recall information we have 2*(20+9)*12 = 696 variables each for the number of shocks and the value of these shocks. To keep the analysis tractable we

[1] Two of these observations are from 1998 – one household in Darmang and one in Pokrom – and one observation was a household in Oboadaka in 2009.

first summed shocks within each household from all respondents in that household. Second, we aggregate shocks across all 12 years. Third, we created summary shock variables for three categories of negative and two categories of positive shocks as described in Table 2. Finally, we created overall variables for the total number of shocks a household experienced and for their total value for each of time period.[2] Our analysis below begins by using these aggregate shocks before disaggregating by category of shock.

Table 2 Categorization of negative and positive shocks

	Family/Personal	Business/Job	Agriculture/Livestock
Negative shocks	death of the household head or spouse, death of a household member, illness of injury o a household member, medical expenses, loss of home, divorce or separation, funeral expenses, division of property, cut-off of remittances, withdrawal of government or NGO assistance	Loss of regular job, loss of productive asset, loss of contract/default, failure/bankruptcy of business	Crop loss due to drought, crop loss due to disease, crop loss due to other reasons, livestock loss due to death, livestock loss due to theft
Positive shocks	New or increased remittances, inheritance, large gift or lottery win, receipt of dowry or brideprice, scholarship for child's education, new government or NGO program	New regular job for household member, young person worked, gain from business activity	

Table 3 gives an overview of the aggregate value and number of negative and positive shocks for households over the period spanned by the panel. Positive shocks were very rare with family and business shocks about equally frequent. The mean number of positive shocks per household over the 12 year period was only 0.2. The value of positive shocks was also very small with an average total of 205 Cedi per household which is only slightly more than the average monthly consumption level of three adults.

Negative shocks were more frequent as well as larger. On average households suffered 1.5 negative shocks between 1998 and 200 losing on average 1206 Cedis. This translates to around US$830 at 2009 prices and is equivalent to about 20 months' average per adult equivalent consumption.

The three categories of negative shocks occurred with different frequencies and exhibited different magnitudes. On average 37% of households suffered from an agricultural or livestock shock. These types of shocks were also smallest in magnitude with an average size of 85 Cedis. 72% of households experienced a family shock. And the average size of family shocks was almost six times as large as the agricultural shocks. This echoes Krishna's (2010) cross-national findings on the relatively high frequency and large magnitude of health and related family shocks on households. The frequency of business

[2] The value of the shocks are self-reported values by the households in response to the question "What was the monetary value of the loss?"

shocks was similar as for agricultural shocks but their value was largest of the three categories at an average of 640 Cedi.

Table 3 Value and Number of negative and positive household level shocks 1998-2009

	Value of Shocks		Number of Shocks	
	Mean	Standard deviation	Mean	Standard deviation
Negative Shocks				
All household shocks	1206	3440	1.51	2.41
Family shocks	480	1781	0.72	1.28
Business shocks	640	2578	0.41	0.97
Agricultural and Livestock shocks	85	314	0.37	0.95
Positive Shocks				
All household shocks	205	1367	0.20	0.64
Family shocks	87	762	0.11	0.40
Business shocks	117	1143	0.09	0.39

The dataset also contains information on different risk management strategies: social networks, self-insurance, access to loans in an emergency, and income diversification.

To capture the effect of the size of respondents' social networks, or their 'social visibility', we summarize each individual's linkages with other survey respondents into an index. In the 1998 survey respondents were presented with seven individuals from the same villages that were randomly drawn without replacement. Respondents then indicated whether they know these random matches.[3] The aggregate of these responses, therefore, contain information on both directions of links between individuals. The random sampling of matches makes the identified links representative of a respondent's extant social links. However, a potential drawback of random sampling is that we might not reliably capture the size of individuals' social networks.

The methodology for collecting the social links that form the basis of our social visibility indices differs between 1998 and 2009. In contrast to the random matching of seven individuals in the 1998 survey the 2009 instrument contains a full census of all social linkages between all respondents in a village. To eliminate differences created by the data collection method that may have exaggerated any prospective change in network sizes over time we rescale the 1998 data by multiplying all 1998 measures by the ratio of the mean of the 2009 and the mean 1998 social visibility index. This also helps to more accurately proxy the size of individuals' social networks in 1998. Even if we don't want to make the strong assumption that mean network size (measured as number of connections) is unchanged over time this still offers a useful approach. This is because our transformation of the 1998 data preserves both the ordering of and the proportional distance between network size measures in the 1998

[3] The survey made the distinction between actually knowing a person and knowing of a person using the Akan translation of "having heard of a person".

observations. The transformed location of that distribution is arbitrary, but its ordering, scale and spread is preserved as is the continuous nature of our social visibility indices.

We used the survey responses to the social network questions to measure an individual's social network in two ways. The first method follows Vanderpuye-Orgle and Barrett (2009) and derives a social visibility index using uni-directional links from all respondents to an individual to calculate the proportion of respondents who know an individual when presented as a random match.

Let *J* be the total number of respondents who were presented with individual *i* as a random match. Let K_{ij} denote an indicator variable equal to one if respondent *j* knows individual *i* and zero otherwise. Then, the one directional social visibility index based on random matches, *D1*, can be expressed as

$$D_1 = \frac{\sum_{j=1}^{J} K_{ij}}{J} \qquad D_1 \in [0,1]$$

Secondly, one can measure social visibility in the other direction, namely the proportion of the matches a respondent knew. Let κ_{ik} be an indicator variable equal to one if respondent *i* knows a presented random match *k* and let K be the number of matches with which an individual was presented. For 1998 K equals 7, for 2009 K is equal to the total population in the village. Then this index takes the form

$$D_2 = \frac{\sum_{k=1}^{K} \kappa_{ik}}{K} \qquad D_2 \in [0,1]$$

Linear combination of the two social visibility indices

$$D = \frac{D_1 + D_2}{2} \qquad D \in [0,1]$$

Another mechanism to insure against risk is to accumulate own savings. We proxy this ability to self-insure by the total amount of the financial savings a household has accumulated. These include funds in *susu*[4], money owed the respondent by others, deposits in bank accounts and holdings of stocks, liquid valuables and currency.

Access to loans in an emergency represents another potential mechanism to cope with negative shocks ex post. This mechanism was captured by asking respondents whether they could obtain a loan of 50 Cedi within a week. From this information we create variable equal to one for households that have such credit access and equal to zero if they don't. Two drawbacks are inherent in measuring credit access this way. First, 50 Cedi is smaller than the total value of all negative shocks reported by any household that experienced at least one shock.[5] Thus, households who could only barely get 50 Cedi

[4] *Susu* is a local form of informal microfinance in which a local collector provides secure savings, and typically limited credit, to depositors.
[5] 50 Cedi represents the 15th percentile of the distribution of all negative shocks but the all households in this percentile had no negative shocks.

would register as 'having access to credit' but the amount of credit was insufficient to overcome their cumulative shocks and, often, individual shocks. Though, of course, some households who responded that they have access to 50 Cedi loans are likely to be able to get much larger loans. For these households our credit access proxy is a more robust indicator of their ability to use loans to mitigate the consequences of shocks. Second, a credit access dummy variable offers only limited variability. We still use this dummy variable in our analysis as the data do not contain any other direct information on potential credit access.

Income diversification provides another mechanism of coping with risk ex ante and ex post. We would expect households with constrained access to other insurance mechanism to rely on a greater diversity of income sources. We measure livelihood diversification in two ways. First, we construct a continuous livelihood diversification index based on the shares of income from five sources: wage income from working for someone else, profits from non-farm businesses, profits from the farm in the village, profits from farms outside the village, and other incomes such as pensions, gift or inheritances, lottery winnings or sales of land. These shares are summarized into a Herfindahl index of income diversification. Let *N* denote the total number of *i* income sources and s_i stand for the share of income source *i* in total household income. Then the index takes the form

$$H = \sum_{i=1}^{N} s_i^2$$

This index is bounded by zero and one[6] and a smaller value of the index implies a higher degree of income diversification.

The second way we model income diversification is through the total number of household income sources. This total number is made up from farm sector diversification, represented by the number of crops sold, non-farm diversification indicating the number of non-farm income sources, the number of sources of labor income, income sources from outside the village and any other sources of income.

The degree of income diversification affects the extent to which a household can self-insurance against income risk within a sector. However, greater diversification does not imply that a household is more likely to participate in higher-return non-farm activities. The continuous nature of the index also means that we don't need to assign households into different diversification categories. Instead we can use it to construct interaction variables with other insurance mechanisms and with shocks.

Table – Descriptive Statistics

Variable	**Unit**	**Mean**	**Std. Dev.**

[6] In the data around one third of households report negative farm profits. For 13% of households these negative farm profits are large enough to make total personal income negative. Since we cannot calculate a Herfindahl index with negative income in the denominator I truncated all sources of personal income at zero. This also means that the households with negative/zero personal income are assigned a Herfindahl diversification index of zero. Given these strong assumptions in calculating the Herfindahl index the subsequent analysis also uses the number of income sources as an alternative measure of income diversification.

Change in monthly household per adult equivalent expenditure (2009-1998)	2009 Cedi	-17	67
household per adult equivalent expenditure 1998	2009 Cedi	66	76
Total value of all negative shocks 1998-2009	2009 Cedi	2412	4564
Total value of all family shocks 1998-2009	2009 Cedi	960	2430
Total value of all business shocks 1998-2009	2009 Cedi	1280	3539
Total value of all agriculture and livestock shocks 1998-2009	2009 Cedi	172	429
Social Visibility of household head	D index	0.67	0.19
Social Visibility of household head	D1 index	0.65	0.20
Social Visibility of household head	D2 index	0.69	0.24
Access to 50 Cedi loan in emergency	Dummy variable	0.87	0.33
Self-insurance (value of household financial savings)	2009 Cedi	1470	2870
Income Diversification	Herfindahl Index	0.72	0.28
Income Diversification	Number of income sources	1.54	1.01
Age of household head	Years	52	12
Grade achieved by household head	Grade	3.66	2.50
Household head occupation		3.74	5.84
Household head was fostered	Dummy variable	0.53	0.50
Household head's family has lived in village long	Dummy variable	0.15	0.36
Household head's mother held village office	Dummy variable	0.06	0.24
Household head's father held village office	Dummy variable	0.23	0.42
Household holds village office	Dummy variable	0.21	0.41

Results: The effect of idiosyncratic shocks and risk management mechanisms

Idiosyncratic shocks have a statistically and economically significant negative effect on household expenditure levels. This result is robust across different time lags and for different types of shocks. The first column in Table 4 summarizes the regression results for shocks that occurred at any time during the panel period 1997-2009. The detailed regression output is given Table 5. The negative effect on household expenditure levels is statistically significant for all shocks and for agricultural and livestock shocks. The estimated effect of business and family shocks is negative, but not statistically significant.

Table 4 Negative shocks and welfare & interactions between negative shocks and insurance mechanisms

	Shock	Shock Interaction terms			
		Credit access	Self-insurance	Social visibility	Income diversification # of income sources
All shocks	-**	+	+**	+*	+
Family shocks	-	+	+**	+	-
Business shocks	-	+	-	-	+
Agriculture and livestock shocks	-**	+	+	+*	-

*** p<0.01, ** p<0.05, * p<0.1

To examine the effectiveness of the different risk management mechanisms on mitigating negative shocks we need to look at the interactions between shocks and the risk management strategies. These interactions are summarized in columns 2-5 in Table 4. The positive signs in column 2 indicate that access to credit helps mitigate the negative effect of all types of shocks, although none of these estimated effects are statistically significant. This could reflect the small sample or the relatively small average effect of shocks on 12-year welfare dynamics and the small effect of modest credit access to protect households' well-being. It could also be because of the loan amount that was asked about in the survey (50 Cedi) was small compared to the shocks suffered by households.

Self-insurance in the form of household savings also helps to reduce the impact of negative shocks. This effect is statistically significant at the 5% level for all shocks and for family shocks even in this small sample. Household savings appear to be insufficient to mitigate the effect of negative business shocks. This may be because, although less frequent, business shocks are on average the largest shocks a household experienced, often caused by failing businesses and unfulfilled contracts in the pineapple industry.

The degree of social visibility has a positive and statistically significant effect on mitigating negative household shocks for shocks overall and for agricultural and livestock shocks. The effect is also positive but not statistically significant for family shocks. And as for self-insurance, social networks do not seem to be strong enough to help overcome large business shocks, although this effect is not statistically significant.

Income diversification has no statistically significant effect mitigating the adverse impact of shocks. Indeed, most of the point estimates are negative. If diversification primarily functions as an income risk reduction strategy then we should expect a positive estimated effect of diversification on mitigating shocks. However, income diversification could also be a reflection of households pursuing multiple low return activities rather than specializing in fewer higher return endeavors. In such a situation the negative effect makes sense: more diversified households get lower returns than less diversified households and therefore are less able to weather shocks. This is the pattern we observe for shocks as a whole and for family and agricultural shocks. The one exception is again with respect to business shocks.

The positive effect of the number of income sources on mitigating the impact of business shocks could reflect the fact that households operating a business use income diversification primarily as an insurance mechanisms for when their main business income falls short.

Table 5 Parametric Regression Results – Interaction of shocks and risk management mechanisms

Interaction Shocks & Mechanisms. Value of Shocks. All years.
Dependent Variable: Change in Expenditure per adult equivalent 1997-2009

VARIABLES	(1) All shocks. Herfindahl	(2) All shocks. # income sources	(3) By shock type. Herfindahl	(4) By shock type. # income sources
monthly HH expenditure 2009 Cedis per adult equivalent lagged one time period	-0.922	-0.683	-0.992	-0.686
	(0.277)	(0.392)	(0.258)	(0.414)
lagged monthly HH expenditure 2009 Cedis per adult equivalent squared	0.00638	0.00254	0.00759	0.00273
	(0.655)	(0.851)	(0.592)	(0.846)
total value of family/personal/social shocks			-0.0607	-0.0564
			(0.224)	(0.276)
total value of family/personal/social shocks squared			-5.63e-07**	-4.00e-07
			(0.0246)	(0.109)
total value of business/job shocks			-0.0158	-0.0141
			(0.542)	(0.478)
total value of business/job shocks squared			4.11e-07**	2.12e-07*
			(0.0177)	(0.0753)
total value of agriculture/livestock shocks			-0.0717**	-0.0761**
			(0.0399)	(0.0177)
total value of agriculture/livestock shocks squared			1.55e-05	1.89e-05
			(0.407)	(0.259)
Mean Social visibility index	75.91	76.16	91.92	85.50
	(0.196)	(0.156)	(0.151)	(0.155)
Mean Social visibility index squared	-106.7**	-95.20**	-119.4*	-109.3*
	(0.0417)	(0.0457)	(0.0566)	(0.0590)
Mean Social visibility index *family shocks			0.00730	0.0151
			(0.645)	(0.385)
Mean Social visibility index *business shocks			-9.04e-05	-0.00772
			(0.990)	(0.315)
Mean Social visibility index *agricultural shocks			0.0568*	0.0376*
			(0.0573)	(0.0807)
Emergency loan (can get GHC50 in a week)	-32.03	-40.74**	-35.29	-44.17*
	(0.127)	(0.0496)	(0.150)	(0.0759)
Emergency loan * family shocks			0.0489	0.0501
			(0.302)	(0.303)
Emergency loan * business shocks			0.0210	0.0173
			(0.366)	(0.373)
Emergency loan * agricultural shocks			0.0317	0.0347
			(0.290)	(0.200)
Self-insurance (financial savings in 1993 PPP$)	0.00736*	0.00941**	0.00582	0.00860
	(0.0861)	(0.0239)	(0.296)	(0.122)

Self-insurance squared	-2.15e-07	-3.11e-07**	-1.70e-07	-2.80e-07
	(0.151)	(0.0369)	(0.378)	(0.148)
Self-insurance * family shocks			3.39e-06**	1.52e-06
			(0.0319)	(0.305)
Self-insurance * business shocks			-4.19e-06	-3.38e-06**
			(0.116)	(0.0111)
Self-insurance * agricultural shocks			6.01e-06	3.17e-06
			(0.534)	(0.758)
income diversification - Herfindahl index	8.825		13.18	
	(0.377)		(0.383)	
Herfindahl * family shocks			0.0116*	
			(0.0791)	
Herfindahl * business shocks			-0.00943	
			(0.171)	
Herfindahl * agricultural shocks_value_ag_all12			-0.0494	
			(0.239)	
All negative shocks (total value)	-0.0359*	-0.0307*		
	(0.0520)	(0.0818)		
All negative shocks squared	-7.34e-08	-2.00e-08		
	(0.364)	(0.807)		
All negative shocks * social visibility index	0.00573*	0.00411		
	(0.0796)	(0.231)		
All negative shocks * emergency loan	0.0277	0.0274		
	(0.124)	(0.109)		
All negative shocks * self-insurance	1.23e-06**	1.66e-07		
	(0.0423)	(0.754)		
All negative shocks * Herfindahl	0.00296			
	(0.148)			
number of income sources		10.77***		10.98***
		(0.00149)		(0.00842)
# income sources * all shocks		-0.000327		
		(0.379)		
# income sources * family shocks				-0.000765
				(0.528)
# income sources * business shocks				0.00134
				(0.145)
# income sources * agricultural shocks				-0.00885
				(0.356)
Observations	126	126	126	126
R-squared	0.746	0.766	0.775	0.791

Robust p-values in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Conclusions

Risk and uncertainty diminish the current level of economic well-being as well as prospects for the future. This is particularly true when livelihood generating activities are highly stochastic, as they are for many rural households in developing countries, and when mechanisms to insure against risk are either non-existent or insufficient. While households face two distinct sources of risk, covariate and idiosyncratic, the latter often dominates and requires different strategies to mitigate.

In this paper we examined the importance of idiosyncratic risk for households in rural Ghana and examined the effectiveness of various risk management strategies in mitigating this risk. The households in our survey have experienced slight improvements in their economic well-being between 1998 and 2009. However, they remain poor with an average expenditure level per adult equivalent of 59 Cedis or $1.35 in 2009 prices. Their estimated long-term future level of well-being is of similar magnitude. Households in the two villages with better access to markets and outside labor opportunities fare considerably better than those in the two more remote communities.

In addition to being poor the survey households face considerable exposure to negative idiosyncratic shocks with the average household losing close to 900 Cedis due to family, business and agriculture and livestock shocks during 1997-2009. Having experienced a shock is strongly related to lower growth in consumption.

Households use a variety of mechanisms to try to prevent and deal with negative shocks including support from social networks, self-insurance in the form of savings, accessing credit and diversifying livelihood activities. Our results suggest varying degrees of effectiveness for these mechanisms. Having own savings and being able to draw on larger social networks offers a statistically significantly better chance of overcoming the consequences of negative shocks. Credit access also seems to help though the evidence is less strong. A greater diversity of income sources is associated with greater gains in expenditure but income diversification does not seem to help in overcoming shocks. This could be a reflection of many households diversifying into low-return activities that are positively correlated.

Overall our results suggest some effectiveness of these formal and informal insurance mechanisms. However, even in their combination they are not sufficient in helping households overcome negative shocks and to ensure sustained improvement in well-being over time.

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Appendix – Controlling for Attrition Bias

We control for attrition bias based on observables following Baulch and Quisumbing (2010).

We first test whether attrition is random using two methods. The first estimates a probit model that tries to explain attrition between 1998 and 2009 through some base period characteristics.

Attrition Probit for Expenditure. Dependent Variable: Attrition Dummy

VARIABLES	(1) Unrestricted Model
age of HH head	0.00445
	(0.717)
squared age	9.71e-06
	(0.990)
highest grade of HH head	0.0241
	(0.706)
HH head in village for longer	-0.306
	(0.111)
fostered HH head	-0.277
	(0.263)
HH size - adult equivalent	0.0278**
	(0.0157)
loglandsize	0.149***
	(0.000588)
lognonland_93dollar	-0.310***
	(9.48e-10)
log_exp_ae_93dollar	-0.142
	(0.451)
mean value of all idiosyncratic HH shocks in village	0.000177***
	(0.00569)
Constant	1.236
	(0.278)
Observations	182

Robust p-values in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- Log pseudolikelihood = -103.51541 Pseudo R2 = 0.1182
- Standard errors adjusted for 4 clusters in village

The pseudo R-squared from the attrition probit indicates what percentage of attrition is explained by the probit (Outes-Leon and Dercon 2008). In table XXX above household and village baseline variables explain about 12 percent of panel attrition between 1998 and 2009. This is reasonably high for an attrition probit but means that 88 percent of attrition is not explained by these variables.

Four variables are statistically significant. A larger household size, larger land holdings and more prevalent shocks in the village makes a household more likely to attrite between 1998 and 2009.

Greater non-land asset holdings make it more likely that a household that was interviewed in 1998 was re-interviewed eleven years later.

The Wald test for joint statistical significance of the variables that can affect attrition has a Chi-squared statistic of 7.97 with 3 degrees of freedom indicating statistical significance at the 5% level. The characteristics of the household head, the level of expenditure in 1998 and the mean value of shocks in the village therefore are predictors of attrition.

The second test for random attrition in our panel uses a pooling test developed by Becketti, Gould, Lillard and Welch (1988). This F-test estimates whether the attrition dummy and the differences in the slope coefficients between attritors and non-attritors are jointly statistically significant.

First we run a regression of expenditure per adult equivalent in 1998 on household and auxiliary variables and their interactions with the attrition dummy. Next we test whether the attrition dummy and all the interactions effects are jointly equal to zero, that is, whether there are statistically significant differences between household that attrite and household that remain in the sample in 2009. The F-statistic of 3.68 can only reject the null hypothesis of random attrition at the 15% level.

Based on this (weak) evidence from the two tests for random attrition we construct inverse probability weights as follows. First we re-estimate the probit from table XXX without the auxiliary variables and construct the predicted values from this restricted model. These predicted values are then divided by the predicted values of the unrestricted probit from table xxx which gives the inverse probability weights that we use to control for attrition in our subsequent calculations.

The resulting attrition weights span from 0.46 to 17.34 with a mean of 1.20.